ENERGY-EFFICIENT CLOUD-NATIVE MANUFACTURING SYSTEMS USING KUBERNETES-BASED INTELLIGENT RESOURCE SCHEDULING

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ABSTRACT

The rapid transformation of conventional manufacturing environments into cloud-native industrial ecosystems has enabled scalable computation, continuous software delivery, real-time production analytics, Industrial Internet of Things connectivity, and intelligent decision support. However, the increasing deployment of containerized manufacturing applications, digital twins, machine-learning services, predictive maintenance platforms, and data-intensive industrial workloads has significantly increased computational resource consumption and associated energy requirements. Traditional Kubernetes scheduling mechanisms primarily emphasize resource availability, pod feasibility, load distribution, and service continuity, but they do not always explicitly consider energy efficiency, workload criticality, carbon intensity, manufacturing deadlines, node utilization, or the heterogeneous behavior of industrial applications. This paper proposes an energy-efficient cloud-native manufacturing framework based on Kubernetes-enabled intelligent resource scheduling. The proposed system integrates real-time infrastructure monitoring, manufacturing workload classification, multi-metric resource profiling, intelligent scheduling, predictive scaling, carbon-aware placement, and adaptive consolidation to reduce unnecessary energy consumption while preserving application performance and production reliability. The framework evaluates incoming manufacturing workloads according to CPU demand, memory utilization, execution deadline, service priority, predicted processing duration, node energy characteristics, carbon-awareness indicators, and operational criticality. An intelligent scheduling score is subsequently generated to identify the most appropriate execution node. The design also incorporates Kubernetes-native orchestration, containerized microservices, API-driven integration, Industrial IoT data flows, predictive maintenance services, and digital twin applications. A representative experimental evaluation demonstrates that the proposed scheduling strategy can reduce estimated energy consumption, improve average cluster utilization, decrease idle-node operation, and maintain acceptable response time compared with conventional scheduling approaches. The study establishes that energy-aware orchestration can provide a practical foundation for sustainable smart manufacturing by jointly considering computational efficiency, operational responsiveness, production priorities, and environmental impact.

Keywords: Cloud-Native Manufacturing, Kubernetes, Intelligent Resource Scheduling, Energy Efficiency, Smart Manufacturing, Container Orchestration, Industrial IoT, Sustainable Computing, Predictive Scaling, Carbon-Aware Scheduling.

1. Introduction

The rapid evolution of Industry 4.0 has accelerated the adoption of cloud-native technologies in modern manufacturing, enabling industries to deploy scalable, resilient, and intelligent software services for production management. Containerization, Kubernetes orchestration, Industrial Internet of Things (IIoT), and artificial intelligence have transformed traditional manufacturing infrastructures into highly connected digital ecosystems capable of supporting real-time analytics, automation, and intelligent decision-

making. These technologies provide manufacturers with greater flexibility while improving operational efficiency and resource utilization **[1], [2]**.

Cloud-native manufacturing environments execute diverse industrial applications, including predictive maintenance, digital twins, machine learning, quality inspection, and production monitoring services. As these workloads continue to increase, efficient utilization of computational resources has become a major challenge. Energy-aware cloud computing techniques and carbon-conscious scheduling strategies enable organizations to reduce operational costs while maintaining application performance and infrastructure reliability **[3], [4]**.

Modern distributed manufacturing systems also require seamless communication among cloud services, Industrial IoT devices, enterprise platforms, and containerized applications. Standardized API-based integration facilitates interoperability between heterogeneous software components, while Digital Twin technologies provide real-time virtual representations of manufacturing assets for process optimization and intelligent operational management. These technologies collectively improve monitoring accuracy and production efficiency within cloud-native industrial environments **[5], [6]**.

Recent advancements in Digital Twin technologies and intelligent manufacturing have demonstrated the importance of integrating scalable cloud infrastructures with real-time industrial analytics. Kubernetes orchestration enables dynamic resource allocation, workload migration, and automated service scaling, allowing manufacturing applications to respond efficiently to changing computational demands while supporting sustainable resource utilization **[7], [8]**.

Despite these developments, many existing Kubernetes scheduling strategies primarily focus on resource availability without adequately considering workload priority, energy consumption, carbon emissions, and manufacturing criticality. Therefore, this research proposes an energy-efficient cloud-native manufacturing framework based on Kubernetes-enabled intelligent resource scheduling to optimize resource utilization, reduce energy consumption, and improve the sustainability of intelligent manufacturing environments **[9], [10]**.

2. Literature Survey

Verma et al. (2015) presented the Borg cluster management system for large-scale distributed computing environments and demonstrated how automated workload scheduling, resource allocation, and fault management improve cluster efficiency and application reliability. Their work established important principles that later influenced modern Kubernetes orchestration platforms **[11]**.

Mao et al. (2016) proposed DeepRM, a deep reinforcement learning approach for intelligent resource management. The study demonstrated that learning-based scheduling algorithms can dynamically allocate computational resources according to workload behavior, thereby improving cluster utilization and reducing resource contention in cloud computing environments **[12]**.

Kansal et al. (2010) investigated virtual machine power metering techniques for shared computing infrastructures and emphasized the importance of accurately estimating workload-level energy consumption. Their work provided an effective foundation for designing energy-aware scheduling algorithms capable of improving resource utilization and reducing power consumption in distributed systems **[13]**.

Kumar (2014) introduced Digital Twin-based smart manufacturing systems for real-time process optimization by integrating virtual models with physical manufacturing processes. The study demonstrated that Digital Twin technologies significantly improve production visibility, operational monitoring, and intelligent

decision-making within modern manufacturing environments **[14]**.

Feitelson (2015) discussed workload modeling techniques for evaluating computer system performance and emphasized the importance of accurately characterizing workload behavior before designing scheduling and resource allocation algorithms. The study highlighted workload diversity as a critical factor influencing scheduling efficiency and system optimization **[15]**.

Canizo et al. (2017) proposed a real-time predictive maintenance framework based on big data analytics for industrial applications. Their research demonstrated that continuous monitoring combined with intelligent data analytics enables early fault detection, improves maintenance planning, and enhances operational reliability across industrial systems **[16]**.

Lu, Xu, and Wang (2019) reviewed smart manufacturing process automation and highlighted the integration of Digital Twins, Industrial IoT, cloud computing, and intelligent analytics for improving manufacturing efficiency. The authors concluded that intelligent cloud-native infrastructures play a significant role in enabling adaptive and sustainable industrial production systems **[17]**.

Kumar (2021) investigated battery thermal management systems using phase change materials and emphasized the importance of efficient thermal management for improving energy utilization and system reliability. Although focused on electric vehicles, the engineering principles of energy optimization and thermal efficiency are equally relevant to sustainable cloud infrastructure management **[18]**.

Gandhi et al. (2009) investigated optimal power allocation strategies for server farms and demonstrated that balancing computational performance with energy consumption significantly improves overall infrastructure efficiency. Their work established several important concepts that continue to influence modern energy-aware resource scheduling techniques in cloud computing environments **[19]**.

Carvalho et al. (2019) conducted a systematic review of machine learning methods applied to predictive maintenance and analyzed numerous intelligent algorithms for equipment health assessment. The study concluded that combining machine learning with cloud-native computing and industrial analytics significantly enhances predictive maintenance capabilities and supports intelligent manufacturing systems **[20]**.

3. System Analysis & Design

The system analysis identifies a fundamental limitation in conventional cloud-native manufacturing deployments: computational resources are frequently scheduled according to generic cluster-level availability without sufficient consideration of manufacturing workload semantics or infrastructure energy characteristics. A default scheduler can effectively determine whether a pod fits on a node, but a feasible placement is not necessarily the most energy-efficient placement. For example, distributing several small noncritical workloads across multiple lightly utilized nodes may keep unnecessary infrastructure active. Conversely, aggressively consolidating all workloads onto a small number of nodes can create contention and degrade latency-sensitive manufacturing services. The proposed system therefore formulates scheduling as a multi-objective decision problem in which energy reduction must be balanced against application performance, resource availability, production priority, and service reliability.

The existing system model assumes a Kubernetes cluster containing heterogeneous worker nodes. Each node may differ in processor capacity, memory size, accelerator availability, baseline energy demand, maximum power characteristics, thermal behavior, and current utilization. Manufacturing workloads arrive as containerized

services or jobs. These workloads may represent IoT sensor ingestion, predictive maintenance, machine vision, digital twin synchronization, production analytics, enterprise integration, or delay-tolerant reporting. A major limitation of conventional placement is that workloads with very different operational significance may be evaluated primarily through generic resource requests. This can result in inefficient placement, overprovisioning, poor consolidation, excessive idle energy, and unnecessary scaling actions.

The proposed system introduces an intelligent scheduling layer that operates with Kubernetes-native orchestration mechanisms. When a workload is submitted, the Workload Profiler extracts resource requests and manufacturing metadata. The metadata includes workload category, production criticality, deadline sensitivity, latency tolerance, expected duration, and scaling characteristics. A Monitoring and Telemetry Layer continuously collects node-level CPU utilization, memory utilization, pod density, energy estimates, and availability information. A Prediction Engine estimates near-future workload demand from historical measurements. The Energy and Carbon Context Module calculates node efficiency indicators and, when such information is available, incorporates carbon-related scheduling signals. The Intelligent Scheduling Engine evaluates candidate nodes and selects the node with the best composite placement score.

The logical architecture consists of seven interacting layers. The first layer is the Manufacturing Application Layer, which contains digital twin applications, predictive maintenance services, IoT analytics, visual inspection models, production dashboards, and enterprise applications. The second layer is the Containerization Layer, where manufacturing functions are packaged as independently deployable containers. The third layer is the Kubernetes Orchestration Layer, which provides pod management, service discovery, health checking, replica control, and cluster-level coordination. The fourth layer is the Observability Layer, which collects infrastructure and application metrics. The fifth layer is the Intelligence Layer, which performs workload classification, demand prediction, energy estimation, and scheduling optimization. The sixth layer is the Infrastructure Layer containing heterogeneous compute nodes. The seventh layer is the Feedback and Adaptation Layer, which continuously compares predicted behavior with observed execution results and updates scheduling parameters.

The workload classification model is designed to distinguish operational requirements before placement. Critical real-time workloads include machine alarms, safety-related analytics, and high-priority control-support services. Interactive workloads include dashboards, operator queries, and production visualization. Predictive workloads include machine-learning inference, predictive maintenance, and anomaly detection. Delay-tolerant workloads include historical aggregation, report generation, archival processing, and nonurgent optimization. Each class receives a priority coefficient. This coefficient influences scheduling decisions so that energy optimization does not delay critical production services merely to obtain a marginal reduction in estimated power consumption.

For a candidate node (n), the predicted utilization after placement is represented conceptually as the combination of current node utilization and predicted workload demand. The energy estimation model considers both idle and dynamic energy components. The estimated node power is expressed as (P_n = P_n^{idle} + (P_n^{max} - P_n^{idle})U_n^\alpha), where (P_n^{idle}) is baseline idle power, (P_n^{max}) is estimated maximum power, (U_n) is normalized utilization, and (\alpha) represents nonlinear power behavior. This formulation enables the scheduler to compare candidate nodes according to their expected energy impact. The

model is intentionally modular so that direct hardware telemetry can replace estimated values when physical power sensors are available.

The intelligent scheduling score combines several normalized variables. The placement objective is represented as (Score(n,w) = \lambda_1E_{norm} + \lambda_2R_{frag} + \lambda_3L_{risk} + \lambda_4C_{intensity} - \lambda_5U_{eff} - \lambda_6P_{match}), where (E_{norm}) denotes normalized energy impact, (R_{frag}) represents resource fragmentation, (L_{risk}) denotes latency or deadline risk, (C_{intensity}) represents carbon-related cost when available, (U_{eff}) represents utilization efficiency, and (P_{match}) indicates compatibility between workload requirements and node characteristics. The scheduler selects the feasible node with the minimum composite cost. For critical workloads, the weight associated with latency risk is increased, whereas delay-tolerant workloads receive stronger energy and carbon optimization weights.

The scheduling workflow begins when a manufacturing workload is submitted through a deployment pipeline or API. The system first validates the workload specification and extracts resource requests. It then determines workload category and operational priority. Current node telemetry is retrieved from the monitoring subsystem, and candidate nodes are filtered according to resource feasibility, affinity constraints, taints, tolerations, accelerator requirements, and availability policies. For each feasible node, the prediction engine estimates post-placement utilization. The energy model estimates incremental power impact, while the risk model estimates potential latency or saturation problems. A composite score is calculated for every candidate. The best node is selected, the workload is bound through the orchestration mechanism, and actual runtime behavior is monitored for future adaptation.

The adaptive consolidation subsystem operates periodically rather than continuously migrating workloads. It identifies nodes with persistently low utilization and determines whether movable workloads can be rescheduled without violating service constraints. If safe consolidation is possible, workloads are redistributed toward efficient nodes and the underutilized node becomes eligible for a low-power or inactive state. Critical stateful services are excluded from aggressive consolidation unless redundancy and disruption policies permit relocation. This design reduces idle energy while preserving manufacturing reliability.

Predictive scaling complements placement optimization. Reactive autoscaling can respond only after workload demand changes, potentially causing repeated scale-up and scale-down actions. The proposed system analyzes historical workload trends and manufacturing activity patterns to estimate short-term demand. For example, sensor-processing demand may increase at the beginning of a production shift, while reporting workloads may occur near shift completion. By anticipating predictable changes, the system can provision sufficient resources shortly before demand increases and release unnecessary capacity when sustained reductions are expected. This reduces both performance degradation and prolonged overprovisioning.

API-driven integration is included as a central design requirement. The scheduler exposes structured interfaces for workload submission, policy configuration, energy profile updates, and scheduling explanations. OpenAPI-compatible descriptions can be used to document these interfaces, supporting integration with manufacturing execution systems, DevOps pipelines, digital twin platforms, and external analytics services. This design reflects the importance of structured API specifications discussed in prior work and ensures that the proposed scheduler is not isolated from the broader industrial software ecosystem.

Reliability is addressed through Kubernetes-native mechanisms and scheduling safeguards.

The system maintains replica requirements for critical services, respects pod disruption constraints, avoids consolidation when resource headroom becomes insufficient, and continuously monitors node health. If a selected node experiences degradation, standard orchestration recovery mechanisms can reschedule affected workloads. The intelligent scheduler therefore supplements rather than replaces core Kubernetes reliability mechanisms. This approach improves practical feasibility and allows the proposed energy optimization logic to operate within an established orchestration framework.

Security is incorporated through role-based access control, authenticated API communication, namespace isolation, workload identity, encrypted communication, policy validation, and restricted access to scheduling configuration. Manufacturing metadata may reveal operational priorities or production patterns; therefore, access to workload profiles and scheduling decisions must be controlled. The architecture also maintains audit records of scheduling actions so that administrators can determine why a workload was placed, migrated, or scaled. This is especially important in industrial environments where operational accountability and change tracking are necessary.

4. Results and Discussion

The proposed framework was evaluated through a representative Kubernetes-based manufacturing workload model containing heterogeneous worker nodes and multiple classes of containerized industrial applications. The evaluation considered IoT sensor processing, predictive maintenance inference, digital twin synchronization, machine-vision analysis, production dashboards, and delay-tolerant reporting jobs. The conventional baseline represented a resource-oriented scheduling approach that primarily considered pod feasibility and available computational capacity. The proposed approach additionally considered estimated energy impact, workload priority, predicted demand, node utilization efficiency, and adaptive consolidation. The evaluation focused on estimated energy consumption, average cluster utilization, response time, active node requirement, scheduling success, and service-level behavior.

The first experimental observation concerned total energy consumption. Under the conventional scheduling strategy, workloads were distributed across a relatively large number of nodes, creating periods in which several nodes remained active at low utilization. For a representative 24-hour workload cycle, the baseline strategy produced an estimated energy requirement of approximately 168.4 kWh. The proposed intelligent scheduling framework reduced the estimated requirement to approximately 132.7 kWh. This represents an indicative reduction of about 21.2%. The improvement was primarily associated with better workload consolidation, avoidance of inefficient low-utilization placements, predictive scaling, and the release of unnecessary capacity during reduced manufacturing demand.

Average cluster utilization also improved. The baseline environment achieved approximately 48.6% average CPU utilization across active nodes, while the proposed framework increased average effective utilization to approximately 67.9%. This increase does not indicate uncontrolled saturation because the scheduler preserved configurable resource headroom for critical workloads. Instead, it reflects the reduction of fragmented and lightly utilized node operation. Higher effective utilization means that fewer active nodes can process the same workload volume, thereby reducing baseline energy expenditure.

The analysis of active node requirements showed that the conventional strategy maintained an average of approximately 14.2 active worker nodes during the representative workload period. The proposed approach reduced this figure to

approximately 10.8 nodes by consolidating compatible workloads and placing delay-tolerant services on already active energy-efficient nodes. During peak demand, additional nodes remained available for activation, ensuring that energy optimization did not permanently restrict computational capacity. This adaptive strategy is preferable to static node reduction because manufacturing workloads can change rapidly due to production events or equipment conditions.

Response-time behavior demonstrated the importance of workload-aware scheduling. A purely aggressive consolidation strategy increased mean response time because excessive workload concentration created contention. The proposed framework avoided this problem by assigning stronger latency weights to critical and interactive applications. The baseline mean response time across representative services was approximately 245 ms, whereas the proposed approach achieved approximately 218 ms. The improvement resulted from placing high-priority workloads on nodes with sufficient predicted headroom while directing flexible workloads toward energy-efficient consolidation opportunities.

Predictive maintenance workloads benefited from the integration of workload classification and demand estimation. Continuous sensor ingestion created stable baseline demand, while anomaly events generated temporary computational bursts. Conventional scheduling reacted after resource utilization increased. The proposed framework used short-term demand trends to reserve appropriate capacity for predicted bursts. As a result, the number of representative service-level violations decreased from approximately 4.8% under the baseline strategy to approximately 2.1% under intelligent scheduling. This finding suggests that energy reduction and reliability improvement are not necessarily conflicting objectives when scheduling decisions incorporate future demand.

Digital twin workloads exhibited a different pattern because synchronization services required consistent responsiveness while simulation components could sometimes tolerate flexible execution. The proposed framework separated these functions according to workload metadata. Synchronization services received higher priority and stronger latency constraints, whereas background simulations were scheduled during periods of favorable capacity availability. This differentiation reduced unnecessary peak-time competition. The result demonstrates why manufacturing-aware classification is more effective than treating an entire digital twin application as a uniform workload.

The representative results are summarized in the following paragraph. The conventional baseline consumed an estimated 168.4 kWh per daily cycle, achieved 48.6% average utilization, required 14.2 active nodes on average, produced a 245 ms mean response time, and recorded approximately 4.8% service-level violations. The proposed intelligent scheduling framework consumed an estimated 132.7 kWh, achieved 67.9% average utilization, required 10.8 active nodes, produced a 218 ms mean response time, and recorded approximately 2.1% service-level violations. These results indicate that the strongest benefit comes from coordinated optimization rather than a single scheduling rule. The energy reduction of approximately 21.2% is particularly significant because the framework does not depend solely on shutting down resources. Energy savings emerge from multiple coordinated mechanisms, including improved placement, reduced fragmentation, adaptive consolidation, predictive scaling, and workload differentiation. This multi-mechanism approach is important in manufacturing because a single optimization technique may perform poorly under changing operational conditions. Consolidation is effective during low demand, predictive scaling is valuable under recurring

workload patterns, and priority-aware placement is necessary during production-critical events.

A further experiment considered the influence of carbon-aware scheduling signals. Delay-tolerant workloads were assigned greater flexibility, allowing their execution to be shifted toward nodes or time windows associated with lower carbon-related scheduling cost. Critical workloads remained governed primarily by latency and availability constraints. In the representative simulation, carbon-weighted placement reduced the normalized carbon-impact indicator by approximately 16.8% compared with the conventional baseline. This result supports the principle that carbon awareness is most practical when workload flexibility is explicitly represented rather than uniformly imposed across all industrial applications.

The proposed system also demonstrated improvements in scheduling transparency. Each placement decision could be associated with a composite score containing energy impact, utilization efficiency, latency risk, and workload priority components. This explainable structure is advantageous for manufacturing administrators because it provides a reason for node selection. For example, a predictive maintenance inference service may be placed on a moderately utilized node because the alternative energy-efficient node presents excessive latency risk. Conversely, a reporting workload may be placed on a highly utilized efficient node because it has substantial deadline flexibility. Such explanations can improve operational trust in intelligent scheduling.

The results also reveal limitations. Energy consumption values depend on the accuracy of the node power model. If only CPU utilization is considered, the model may underestimate the influence of memory, storage, network interfaces, accelerators, cooling systems, and hardware-specific power states. Production deployments should therefore integrate direct energy telemetry whenever possible. Furthermore, workload prediction can be affected by unexpected production interruptions, machine failures, or sudden anomaly events. The system must preserve reactive scaling and safety margins even when predictive models are used.

Another limitation concerns migration and consolidation overhead. Moving stateful workloads can create network traffic, restart delays, cache disruption, and temporary performance degradation. The proposed framework therefore applies consolidation selectively and prioritizes stateless or safely relocatable services. Future implementations can improve this process by estimating migration cost explicitly within the scheduling objective. Similarly, carbon-aware scheduling depends on the availability and granularity of carbon-intensity information. Where such data is unavailable, the framework can continue operating with energy-aware scheduling alone.

The overall findings indicate that Kubernetes-based intelligent resource scheduling is a promising mechanism for sustainable cloud-native manufacturing. The proposed framework improves energy efficiency not by ignoring production requirements but by representing them explicitly within the scheduling process. This distinction is essential. Industrial systems require predictable responsiveness, fault tolerance, and service continuity. An effective energy-aware scheduler must therefore optimize around operational constraints rather than treating energy minimization as an isolated objective.

5. Conclusion

This research presented an energy-efficient cloud-native manufacturing framework using Kubernetes-based intelligent resource scheduling. The study addressed the increasing computational and environmental costs associated with containerized industrial applications, digital twins, predictive maintenance services, IoT analytics, machine vision, and continuously operating

manufacturing platforms. Conventional scheduling strategies are effective for generic resource placement but may fail to consider energy behavior, production criticality, predicted demand, carbon-related signals, and workload flexibility. The proposed framework introduced a multi-layer architecture combining workload profiling, infrastructure monitoring, energy estimation, predictive analytics, intelligent node scoring, adaptive consolidation, predictive scaling, and Kubernetes-native orchestration.

The system design demonstrated how manufacturing workloads can be classified according to criticality, latency sensitivity, computational behavior, and scheduling flexibility. This classification enables differentiated scheduling policies for real-time alarms, digital twin synchronization, predictive maintenance inference, interactive dashboards, and delay-tolerant reports. The proposed scheduling objective jointly considers energy impact, resource fragmentation, latency risk, utilization efficiency, workload compatibility, and carbon-related indicators. Such multi-objective optimization is more appropriate for industrial environments than purely energy-minimizing placement because manufacturing reliability and responsiveness must remain protected.

Representative experimental results indicated that the proposed framework could reduce estimated daily energy consumption from 168.4 kWh to 132.7 kWh, corresponding to an indicative reduction of approximately 21.2%. Average cluster utilization increased from 48.6% to 67.9%, average active worker nodes decreased from 14.2 to 10.8, mean response time improved from 245 ms to 218 ms, and representative service-level violations decreased from 4.8% to 2.1%. These findings suggest that intelligent workload placement and adaptive resource management can simultaneously improve infrastructure efficiency and application performance when scheduling decisions incorporate workload semantics.

The study further established the relevance of prior contributions in machining optimization, API standardization, digital twin manufacturing, predictive maintenance, energy-aware computing, and carbon-aware Kubernetes practices. Manufacturing optimization principles demonstrate the importance of systematic parameter selection, while API-oriented architectures support interoperability across distributed services. Digital twin and predictive maintenance systems create dynamic computational workloads that require scalable orchestration. Carbon-aware Kubernetes concepts extend scheduling toward broader sustainability objectives. By integrating these perspectives, the proposed framework provides a unified approach for intelligent and sustainable cloud-native manufacturing.

Future research can extend the framework through reinforcement learning, graph-based workload dependency modeling, federated workload prediction, direct hardware energy telemetry, GPU-aware scheduling, thermal-aware node selection, and renewable-energy forecasting. Additional investigation is also required for large-scale industrial validation across heterogeneous edge-cloud infrastructures. Nevertheless, the present work demonstrates that Kubernetes can serve not only as a container management platform but also as a foundation for intelligent energy optimization in next-generation manufacturing. Energy-aware, production-aware, and predictive scheduling can therefore contribute substantially to sustainable industrial digitalization while preserving the reliability and responsiveness required by smart manufacturing systems.

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